



ORIGINAL RESEARCH ARTICLE

A HILBERT-WAVELET FUSION FOR ENHANCED WIDEBAND SPECTRUM SENSING IN COGNITIVE RADIO

S. B. Joseph^{1*}, D. P. Yusuf¹, E. G. Dada², L. L. Muzong¹

¹ Department of Computer Engineering, Faculty of Engineering, University of Maiduguri, Maiduguri, Nigeria

² Department of Mathematical Sciences, Faculty of Science, University of Maiduguri, Maiduguri, Nigeria

*Corresponding author's email: sjbassi74@unimaid.edu.ng

ARTICLE INFORMATION

Received: 17th December 2025
Revised: 19th January 2026
Accepted: 2nd February 2026

Keywords:

Cognitive radio
Hilbert transform
Spectrum sensing
Wavelet

ABSTRACT

The rapid growth of wireless technology has escalated demand for the finite radio spectrum. Cognitive Radio addresses this by enabling dynamic access to underutilized bands, yet its effectiveness depends on accurate spectrum sensing. Current sensing methods often suffer from poor performance in noisy environments and low-signal conditions, creating a critical reliability gap. This study presents an enhanced sensing technique that integrates the Hilbert Transform with Discrete Wavelet Packet Transform. The hybrid design sharpens signal analysis across sub-bands, and an adaptive threshold mechanism improves vacancy detection. The system was rigorously evaluated through simulation. Key results demonstrate a significant performance improvement. The proposed technique achieves, on average, a 77% better signal representation across decomposed channels compared to conventional wavelet sensing. Furthermore, Receiver Operating Characteristic (ROC) curves confirm a higher probability of detection at signal-to-noise ratios of -5dB, 0dB, and 5dB. These metrics substantiate that the fused method offers superior detection capability and reliability. The work provides a validated approach for making cognitive radio networks more robust and spectrum utilization more efficient.

© 2026 Faculty of Engineering, University of Maiduguri, Nigeria. All rights reserved.

1.0 Introduction

The unprecedented growth in wireless communication has created a pressing demand for the finite resource of radio spectrum (Akyildiz, Kak & Nie, 2020). Contemporary networks predominantly rely on a static allocation model, where specific frequency bands are permanently licensed to specific services. This fixed structure, combined with limited coordination between devices, leads to significant underutilization, with large portions of the spectrum idle at any given time and location (Zhang, Liang & Xiao, 2018; Aloqaily et al. 2020; Iqbal et al., 2025). These underutilized bands, termed "spectrum holes," represent a critical opportunity for improved efficiency. Cognitive Radio (CR) has emerged as the intelligent solution to this problem (Vithalani & Vithalani, 2021). A CR device can autonomously sense its radio environment, identify these spectrum holes, and temporarily access them for communication without causing harmful interference to licensed primary users. This dynamic spectrum access paradigm promises to revolutionize spectral efficiency. The entire CR operation hinges on one fundamental task: spectrum sensing (Gbenga-Ilori et al., 2025). The reliability of the system depends on the sensor's ability to make fast, accurate decisions, characterized by a high probability of detecting a primary user and a very low probability of false alarm, as mandated by standards like IEEE 802.22 (Gbenga-Ilori et al., 2025). An illustration of the main tasks of a CR which includes spectrum sensing, spectrum decision, spectrum mobility and spectrum sharing and their relationship is presented in Figure 1.

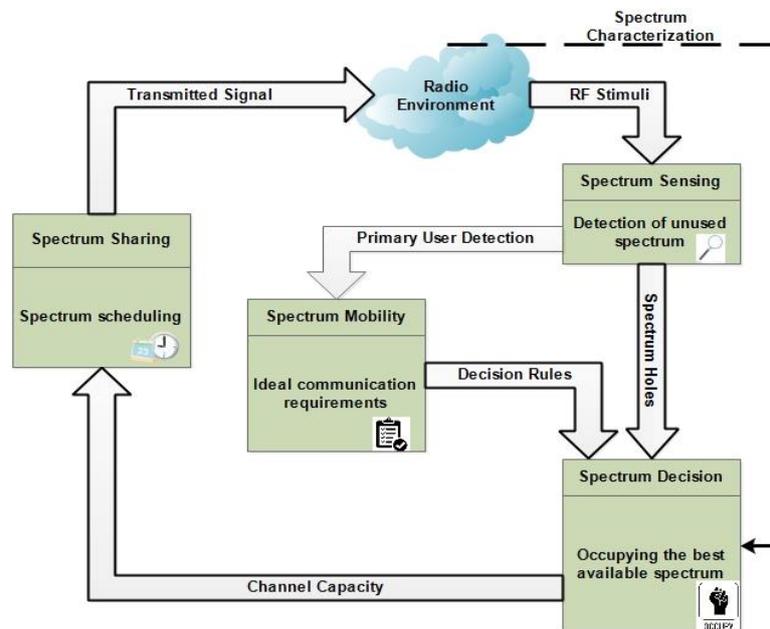


Figure 1: Cognitive radio cycle

The quest for reliable sensing has yielded several methodologies, each with inherent compromises such as matched filter detection. While theoretically optimal, this method requires precise prior knowledge of the primary signal's characteristics, such as modulation type and pulse shape, which is often unavailable in practice (Kang, Sharma and Singh, 2017; Chantaraskul and Moessner, 2009). Another is cyclostationary feature detection. This technique exploits inherent periodicities in modulated signals, making it robust to noise. However, it also requires prior signal knowledge and suffers from high computational complexity (Liu *et al.*, 2015; Panaitopol, Datta, and Fettweis, 2012). Also, energy detection. The most widely used method due to its simplicity and non-coherent nature - it requires no prior signal information (Chantaraskul and Moessner, 2009). Its major drawbacks are severe performance degradation in low signal-to-noise ratio (SNR) conditions and an inability to distinguish between a primary user's signal and noise (Zhang and Qin, 2010; Abdulsattar and Hussein, 2012). Cooperative Detection is another method. This approach improves reliability by fusing sensing data from multiple CR users. However, it introduces significant communication overhead, latency, and increased system complexity (Chantaraskul and Moessner, 2009). A common limitation across these classic methods is their primary suitability for narrow-band sensing. To effectively find opportunities in a crowded spectrum, wideband sensing - scanning a large contiguous frequency range - becomes essential (Chantaraskul and Moessner, 2009). Furthermore, performance under noise uncertainty and low-SNR conditions remains a pervasive challenge (Sawant and Kumbhar, 2012; Iqbal *et al.*, 2025).

Wavelet transforms introduced a paradigm shift for wideband sensing. Unlike conventional methods that require banks of narrowband filters, wavelet-based techniques can analyze a wide frequency range simultaneously, offering a more flexible and potentially cost-effective solution (Iqbal *et al.*, 2025; Jindal, Dass, and Gangopadhyay, 2014). The core idea is to decompose the received wideband signal into different frequency sub-bands, effectively detecting the "edges" between occupied and vacant channels. Initial research focused on the Discrete Wavelet Transform (DWT). While promising, a significant flaw was identified: DWT provides fine resolution only for low-frequency sub-bands, while high-frequency bands are poorly resolved, leading to a loss of signal fidelity (Sawant and Kumbhar, 2012; Iqbal *et al.*, 2025). Enhancements like combining DWT with Eigen filters improved detection in low bands but did not solve this high-frequency resolution problem (Varadharajan and Rajkumari, 2012). To overcome DWT's limitation, the Discrete Wavelet Packet Transform (DWPT) was adopted. DWPT recursively decomposes both the high- and low-frequency components, providing a full, balanced analysis of the entire spectrum and preserving signal fidelity across all bands (Kang, Sharma, and Singh 2017; Zhang and Qin 2010). This made DWPT a strong foundation for wideband sensing. However, many systems that paired DWPT with a simple energy detector remained vulnerable to performance degradation in low-SNR conditions, a critical real-world scenario (Dakshata and Vineeta, 2016). An illustration of spectrum band with white holes is presented in Figure 2.

Parallel research explored the Continuous Wavelet Transform (CWT) for its superior accuracy in detecting signal edges and its sampling flexibility (Zhang, Liang & Xiao, 2018). Studies demonstrated that CWT could achieve good detection accuracy even when signals were close to noise levels (Almeida *et al.*, 2008), and modifications like using its first-order derivative improved edge detection further (Chantaraskul and Moessner,

2009). However, a critical flaw emerged: CWT is computationally intensive due to its inherent redundancies, making it impractical for real-time processing in power-constrained CR devices (Instruments, 2019). This trade-off between accuracy and feasibility rendered pure CWT-based approaches unsuitable for practical deployment.

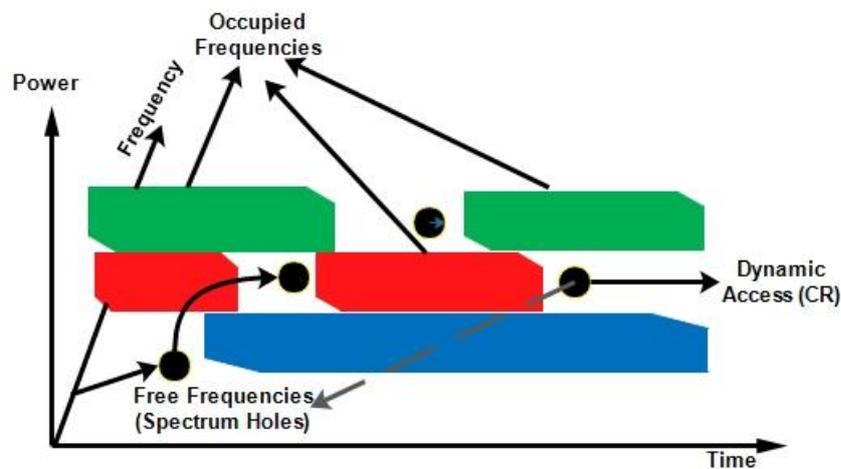


Figure 2: Cognitive radio spectrum band with white holes

While the imperative for robust spectrum sensing is clear, existing techniques reveal a significant performance gap, particularly for wideband sensing in real-world conditions. Traditional methods like matched filtering and cyclostationary detection require prior knowledge of primary user signals, which is often impractical (Kang, Sharma and Singh, 2017). The simpler energy detection approach fails in low signal-to-noise ratio (SNR) environments and cannot distinguish between noise and actual signals (Iqbal *et al.*, 2025). Although wavelet-based methods, especially those using the Discrete Wavelet Packet Transform (DWPT), offer a promising framework for wideband analysis without prior information, they still exhibit key weaknesses. Standalone DWPT-based sensing often demonstrates poor performance under noise uncertainty and low-SNR conditions (Sawant and Kumbhar, 2012; Dakshata and Vineeta, 2016).

Furthermore, proposed enhancements to improve accuracy tend to introduce new drawbacks. Techniques incorporating the Continuous Wavelet Transform (CWT) or complex cooperative mechanisms achieve better detection at the cost of prohibitive computational complexity and overhead, rendering them unsuitable for real-time, resource-constrained CR devices (Instruments, 2019; Chantaraskul and Moessner, 2009). Therefore, a critical gap exists there is a need for a practical, wideband spectrum sensing scheme that maintains low computational complexity while significantly improving detection reliability and noise resilience, particularly in low-SNR scenarios. This work directly addresses this gap by proposing and evaluating an enhanced sensing architecture that strategically combines the full-spectrum analysis of DWPT with the sharp signal characterization of the Hilbert Transform, alongside an adaptive thresholding mechanism, to achieve superior performance without sacrificing practical implementability. The search for an optimal balance spurred the development of hybrid models that combine the strengths of different tools:

- DWPT with Enhanced Detectors: DWPT was integrated with cyclostationary detectors or double-threshold methods to improve accuracy, though often at the cost of increased sensing time or continued need for prior signal knowledge (Adoum, Mossa, and Jeoti, 2010; Kim *et al.*, 2008).
- The Hilbert Transform Advantage: The Hilbert Transform entered the field as a powerful mathematical tool renowned for creating sharp, analytic signal representations. Its ability to detect subtle phase and frequency changes makes it ideal for identifying precise spectral boundaries (Jeng *et al.*, 2011).
- Initial Hybrid Attempts: Pioneering work combined the Hilbert Transform with CWT, achieving excellent edge detection for wideband sensing. Unfortunately, this hybrid inherited CWT's computational burden, limiting its real-time applicability (Jeng *et al.*, 2011). Another study paired the Hilbert Transform with DWT, which improved low-SNR performance but failed to solve DWT's inherent high-frequency resolution problem (Sarker, 2016).

The most promising recent advancement is the fusion of DWPT with the Hilbert Transform. Research indicates this hybrid leverages the complementary strengths of both: DWPT provides efficient, full-spectrum decomposition with balanced resolution, while the Hilbert Transform sharpens the analysis within each sub-

band for superior edge detection (Dibal et al., 2018). This combination directly addresses the dual challenge of achieving high signal fidelity across all frequencies and maintaining robustness in noisy environments. The trajectory of research clearly shows a progression from simple, flawed methods toward sophisticated hybrids. The current frontier is defined by the pursuit of a sensing system that leverages the analytical power of tools like the Hilbert Transform and DWPT while actively addressing the practical constraints of computational complexity and real-time processing speed, paving the way for the practical realization of efficient cognitive radio networks. The remainder of this paper is organized as follows. Section 2 explores related spectrum sensing techniques for cognitive radio. Section 3 presents the proposed spectrum sensing scheme. Performance evaluation of the proposed sensing scheme is presented in Section 4. Section 5 draws the conclusion and presents recommendations for future work.

2. Materials and Method

In an effort to improve cognitive radio's spectrum identification and utilisation capabilities, this paper suggests an improved spectrum recognition and negotiation system. A block representation of the proposed scheme is depicted in Figure 3 to illustrate the big picture of the scheme. The proposed scheme block representation is composed of three (3) phases. The input phase involves generation of individual real sinusoidal sine wave signals, combined together to form a single real discrete wideband signal as input to the system. The process phase is composed of Additive White Gaussian Noise (AWGN) which adds a Gaussian noise, Discrete Wavelet Packet Transform (DWPT) for decomposition into sub-bands, Hilbert Transform improvement of signal representation and detection of sub-bands and lastly thresholding, threshold at each node is estimated using adaptive threshold dynamically and multiplied by a threshold factor to investigate the impact of threshold on detection. The output phase for decision making based on either a channel is vacant or occupied by a primary user.

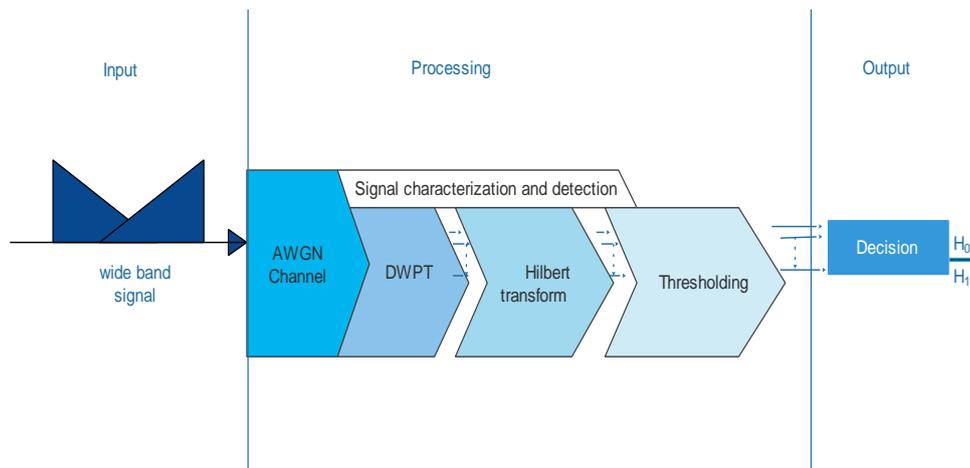


Figure 3: System block diagram

2.1 Wavelet Based Spectrum Sensing for Cognitive Radio

The architectural Conceptual model of the proposed enhanced wavelet-based spectrum sensing using Hilbert transform is presented in Figure 4. A real sinusoidal sine wave signal is generated defined by an expression of the type in as given by Equation 1. A set of sinusoidal signals for analysis were generated using MATLAB. Table 1 presents generated signals forming the required real discrete wideband spectrum that was used for the analysis. AWGN channel adds Gaussian noise to the incoming signal to mimic the real-life random process that affects wideband signal. In this work, AWGN of -10db was added to the original signal to model a real-life wideband spectrum. Discrete Wavelet Transform decomposes input wideband signal into sub-bands with smaller bandwidths and slower sample rates. The analysis of the signal is carried firstly by decomposing the signal into approximation space (low pass frequency component) and detail space (high pass frequency component). Deubechies of order 4 (db4) were used for level 4 decomposition to generate 16 wavelet packets coefficients having different power spectral densities (PSD) as shown in Figure 5. Inputs are always interpreted as frames. The frame size must be a multiple of $2n$, where n is the number of levels of decomposition.

$$y = A \sin(2\pi ft + \phi)$$

1

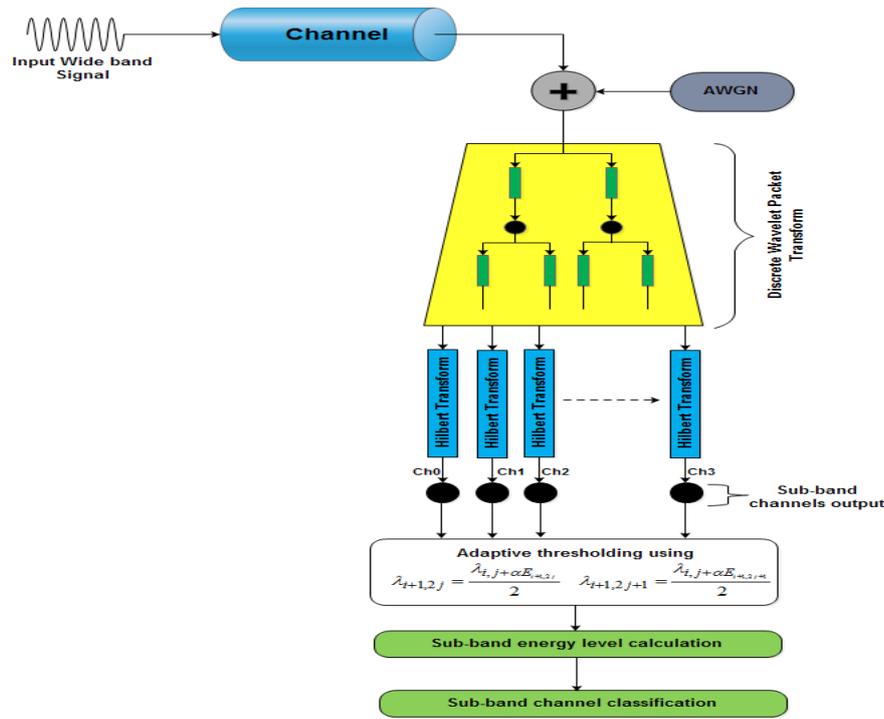


Figure 4: System architectural concept model

Energy in each sub-band channel is estimated by Equation 2 and Equation 3 as presented in (Qin et al. 2012). Where c_{j,k^2} and d_{j,k^2} are the scaling and wavelet coefficients respectively. While threshold for a sub-band channel in the DWPT tree can be computed using Equation 4 and Equation 5. Where $(j = 0, 1, \dots, 2^i - 1)$ is the number of channels at the $(i + 1)th$ level of decomposition, $\lambda_{i,j}$ is the threshold associated with the parent node, $\lambda_{i+1,2j}$ and $\lambda_{i+1,2j+1}$ are the thresholds associated with the two child nodes from the same parent node at the $(i + 1)th$ level of DWPT decomposition. $E_{i+1,2j}$ and $E_{i+1,2j+1}$ are the energies associated with the two child nodes at the $(i + 1)th$ level of decomposition, while α is a tuning factor which makes the received energy have a profound effect on the adaptive threshold if it tends to 1.

$$E = \frac{1}{T} \int_0^T [\sum_{j \geq j_0} \sum_k c_{j,k} \phi_{j,k}(t) + d_{j,k} \psi_{j,k}]^2 dt \tag{2}$$

$$E = \frac{1}{T} \sum_{j \geq j_0} \sum_k (c_{j,k}^2 + d_{j,k}^2) \tag{3}$$

Channel classification is carried out by comparing the power spectral density of each sub-band channel against its threshold and the right decision about spectrum occupancy is obtained using Equation 6 and Equation 7 as suggested in (Jiang et al. 2011). Assuming primary signal is termed $s(n)$, $w(n)$ is AWGN with zero mean of ρ^2 , and N sampling number hence $x(n) = s(n) + w(n)$, $n = 0, 1, \dots, N - 1$. The primary user problem can be modeled as a binary hypothesis testing problem.

Table I: Generate sinusoidal signals with their corresponding parameters

S/No.	Signal	Amplitude/(m)	Frequency / (MHZ)
1	x1	1.3	31
2	x2	2.5	51
3	x3	1.7	70
4	x4	1.9	100
5	x5	1.3	131
6	x6	2.0	180
7	x7	1.8	233

$$\lambda_{i+1,2j} = \frac{\lambda_{i,j} + \alpha E_{i+1,2j}}{2} \tag{4}$$

$$\lambda_{i+1,2j+1} = \frac{\lambda_{i,j} + \alpha E_{i+1,2j+1}}{2}$$

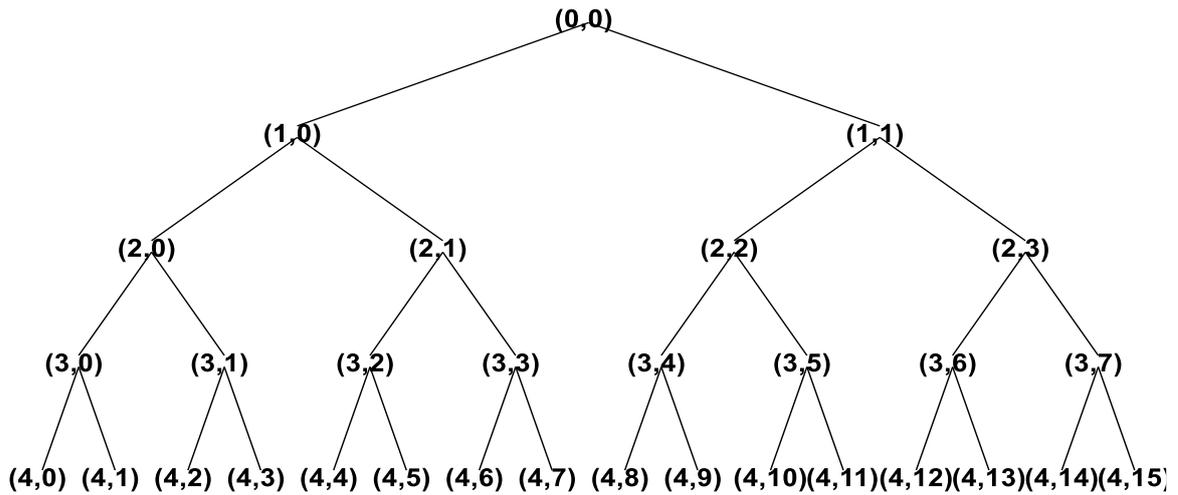


Figure 5: Wavelet packet tree for level 4 decomposition

$$H_0: x(n) = w(n), \quad n = 0, 1, \dots, N - 1 \tag{6}$$

$$H_1: x(n) = s(n) + w(n), \quad n = 0, 1, \dots, N - 1 \tag{7}$$

Where H_0 represents an occupied channel and H_1 represents an occupied channel.

2.2 Proposed Algorithm

In order to improve the wavelet-based spectrum sensing, an enhanced algorithm was designed. In the proposed algorithm Hilbert transform is used to improve received signal representation and enhance ability to detect subtle changes in the received signal, and adaptive threshold was used to enhance spectrum vacancy decision. Algorithm 1 presents proposed improved wavelet-based spectrum sensing algorithm using Hilbert Transform. The flowchart representation of the proposed algorithm is presented in Figure 6.

Algorithm 1: Discrete Wavelet Packet Transform-Spectrum Hole Identification

- 1: Generate real sinusoidal sine wave signals using $y = A \sin(2\pi f t + \rho)$ \triangleright A is amplitude, f is the frequency, t is the sample time and ρ is the phase shift
- 2: Perform Hilbert transform of the discrete wavelet packet decomposed signal
- 3: Extract all coefficients in sub-band channels of wavelet packet tree \triangleright channel-by-channel
- 4: Compute the Energy E_i using Equations 2 & 3 \triangleright for each sub-band channel of wavelet packet tree
- 5: Generate adaptive threshold using equation 8 \triangleright for each sub-band channel
- 6: Threshold the coefficients in channel i against the computed threshold λ_i using equation 9
- 7: Generate histogram for all sub-band channels
- 8: **if** Signal Energy \geq Threshold **then**
- 9: Classify Channel as Occupied
- 10: **else**
- 11: Classify Channel as Vacant
- 12: **end if**

Generate real sinusoidal sine wave signals using $y = A \sin(2\pi f t + \rho)$ Perform Hilbert transform of the discrete wavelet packet decomposed signal Extract all coefficients in sub-band channels of wavelet packet tree Compute the Energy E_i using Equations 2 & 3 for each sub-band channel of wavelet packet tree Generate adaptive threshold using Equation 8 Threshold the coefficients in channel i against the computed threshold λ_i using Equation 9 Generate histogram for all sub-band channels Classify Channel as Occupied Classify Channel as Vacant

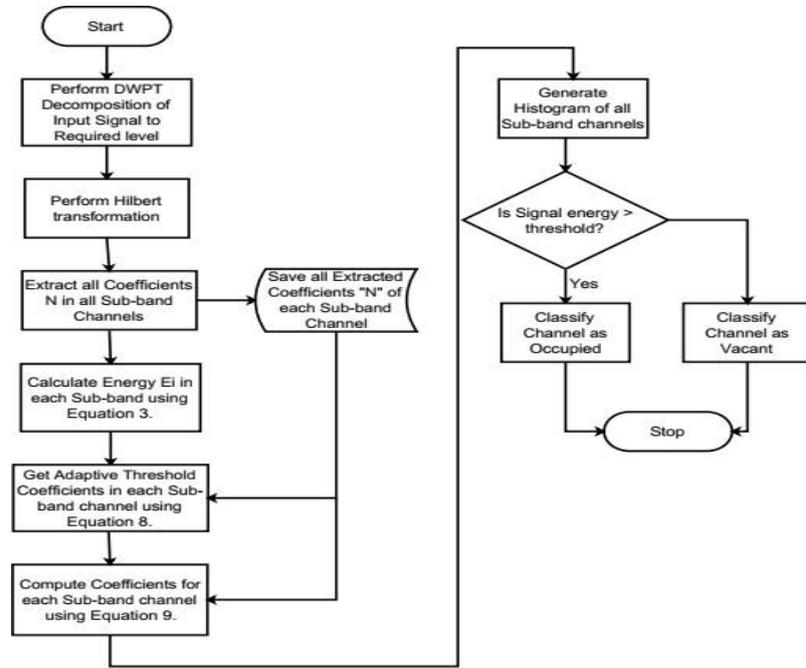


Figure 6: Flowchart for proposed improved wavelet-based spectrum sensing using Hilbert transform

The adaptive threshold for each sub-band channel can be computed using Equation 8 as suggested in (Gao et al. 2015).

$$\lambda_i = \rho_i \sqrt{2 \log N_i} \tag{8}$$

The threshold coefficients of a channel i against the computed threshold λ_i can be computed using Equation 9. Where w_i is the wavelet packet coefficient in channel i before thresholding, w_{λ_i} is the wavelet packet coefficient in channel after thresholding.

$$w_{\lambda_i} = \begin{cases} w_i, & |w_i| \geq \lambda_i \\ 0, & |w_i| < \lambda_i. \end{cases} \tag{9}$$

2.3 Evaluation Metrics

To evaluate the performance of the proposed scheme against the state of the art, receiver operating characteristics (ROC) curve, a graph of the probability of detection, P_d plotted against the probability of false alarm, P_{fa} in varying decision threshold is used. Probability of detection refers to probability of the secondary user declaring presence of primary user in each channel when in fact the channel is occupied. This is represented by the hypothesis expression in Equation 10 as presented by (Li and Li 2015).

$$P_d = Prob(H_1|H_1) \tag{10}$$

Where, H_1/H_0 represents the presence and absence of primary user respectively. The higher P_d , better the protection of primary user against interference. Probability of false alarm P_{fa} is the probability that a secondary user declares presence of primary user in each channel when the spectrum in reality is not in use. This is represented by the hypothesis expression in Equation 11.

$$P_{fa} = Prob(H_1|H_0) \tag{11}$$

3. Results and Discussion

This section presents the results obtained towards the achievement of all set objectives; wideband signal generation; sub-band channel coefficients of DWPT input signal into 16 channels; sub-band channel coefficients of channel 1-16 at 0dB showing signal representation of referred scheme and this work; Hilbert transform based spectrum sensing at -10dB, -5dB, 0dB and 5dB; Receiver Operating Characteristics (ROC) curves

for probability of detection against false alarm and probability of detection against Signal-to-Noise ratio; and the performance evaluation of this work and the referred scheme.

3.1 Wideband Signal Generation

Wideband signal was successfully generated using multiple narrow band signals combined and the resulting signal before and after the effect of AWGN at $-10dB$ is presented in Figure 7. This serves as a channel model that mimics random processes which affect wideband signal generation. The resultant signal provides us with mathematical models that helps in gaining insight into the behavior of the system;

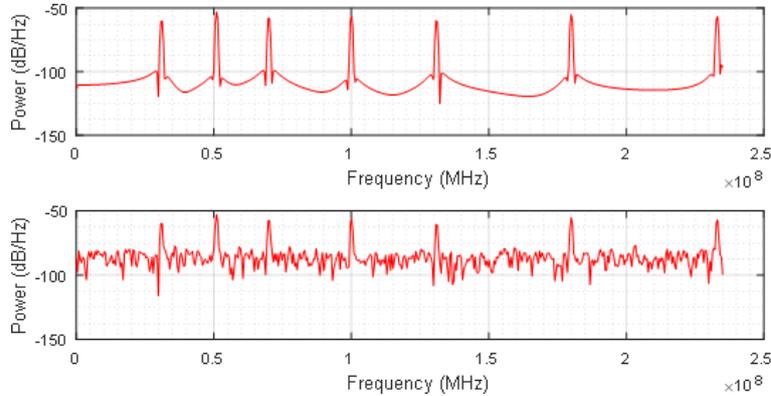


Figure 7: Wideband Signal Generation without AWGN and with AWGN

3.2 Sub-band channel coefficients of DWPT input signal into 16 channels

To design a wavelet-based spectrum sensing with high fidelity, both the band pass of input wideband signal must be decomposed and each channel analyzed for spectrum holes. Daubechies 4 (daub4) family of DWPT was used in 4-level decomposition of the input signal into 16 distinct channels having different power spectral density (PSD). The energy of coefficients depicts the presence or absence of an active user. Figure 8 illustrates selected distribution of sub-band coefficients with different magnitudes.

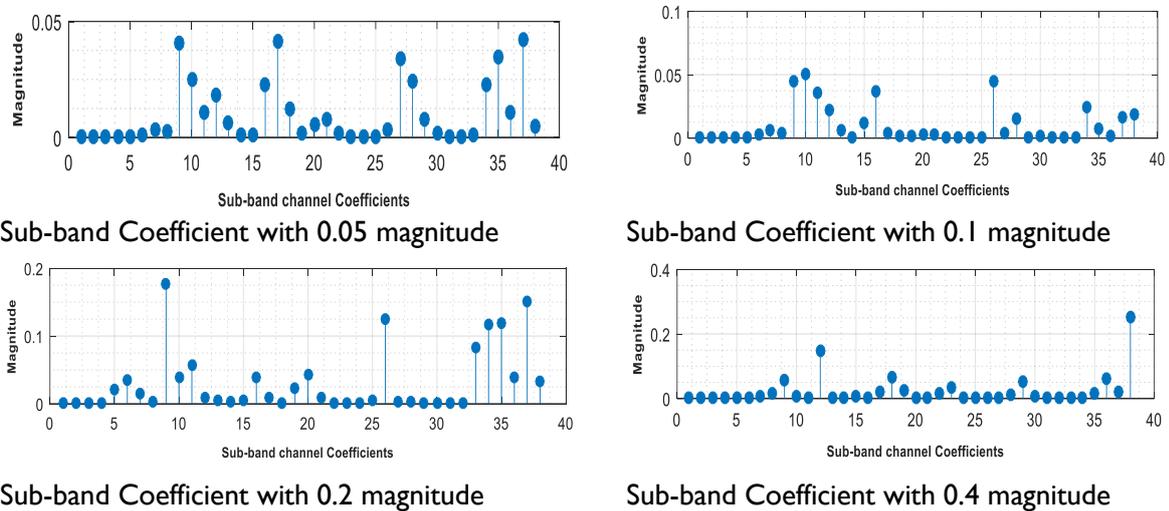


Figure 8: Illustration of sub-band channel coefficients of DWPT

3.3 Sub-band Channel Coefficients with Hilbert Transform and DWPT

This section demonstrates the superiority of introducing Hilbert transform in detecting signals with abrupt changes. To achieve this goal sub-band channels coefficients were plotted using DWPT alone against Hilbert transform based DWPT at $0dB$. A composite plot in Figure 9 illustrates a comparison of DWPT signal sensing vs HT/DWPT sensing for different channels and magnitudes.

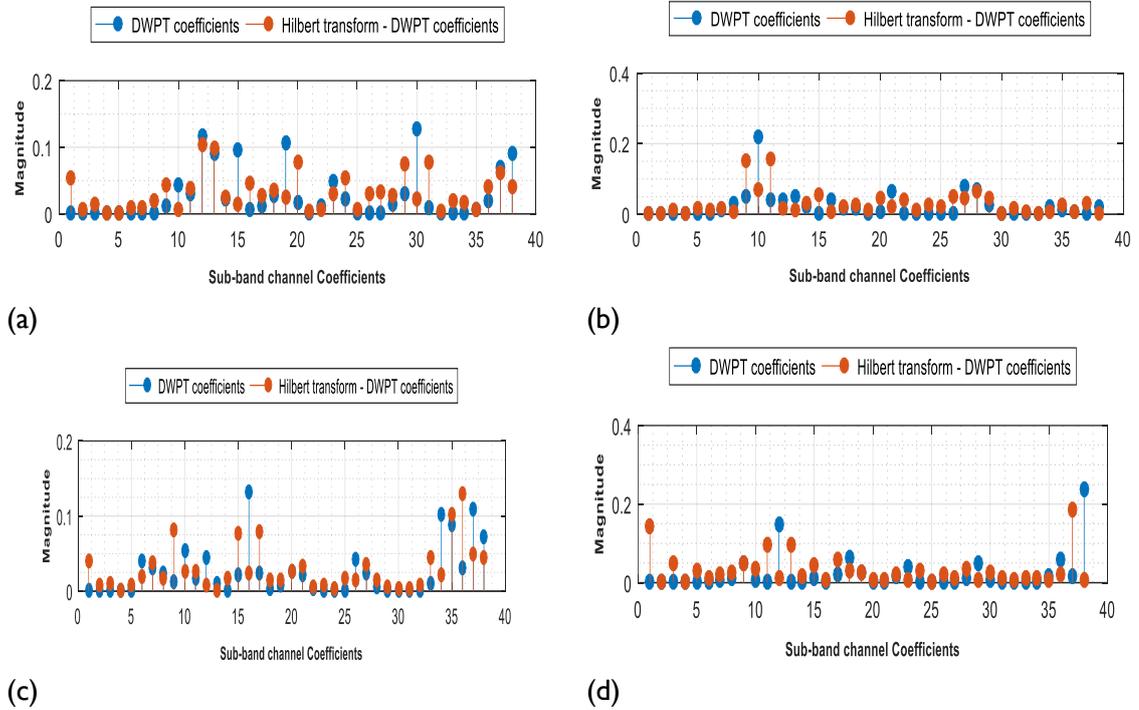


Figure 9: Comparison of sensing capabilities of DWPT and HT-DWPT

The results in Figure 9a shows a 76% percentage where 29 of 38 of the coefficients show better signal representation by Hilbert transform (HT) based DWPT than when DWPT is used alone. Better signal representation is key in improving the accuracy of probability of detection and lowering the probability of false alarm in a spectrum sensing system. Figure 9b shows the result for a different channel with 74% where 28 of 38 of the coefficients of channel 2 are better represented by Hilbert transform based DWPT as shown. Channel three (3) in Figure 9c gives a performance of 82% (31 of 38) by combining HT and DWPT. In Figure 9d a performance of 87% (33 of 38) is better represented by Hilbert transform based DWPT compared to when DWPT is used alone as illustrated. Hence, the results show that the inclusion of HT to DWPT for sensing is a promising technique for cognitive radio spectrum sensing.

3.4 DWPT Based Spectrum Sensing Using Hilbert Transform at Different SNR

This section presents results of spectrum sensing using different values of SNR and using Equations 4 and 5 to measure the performance of the proposed sensing strategy. Figure 10 depicts result for -10dB which indicates only sub-band 14 was identified as a vacant channel.

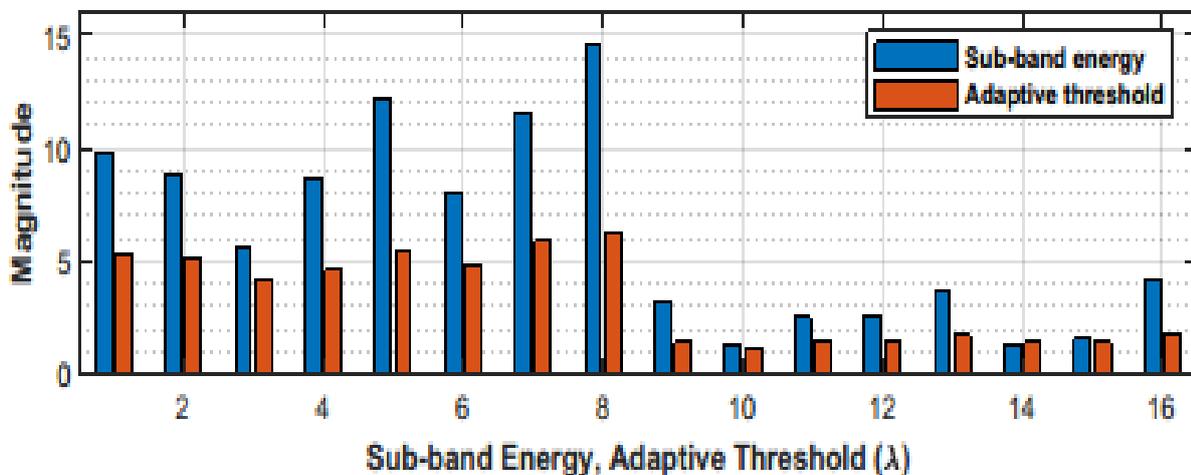


Figure 10: HT-DWPT Spectrum sensing at -10dB

The SNR value increased to -5dB , and spectrum sensing was performed as shown in Figure 11 showing two (2) unoccupied channels (10 and 14) detected. The increase in SNR from -10dB to -5dB caused an increase in

energy in the sub-band channels. With this increase, the adaptive thresholds in each sub-band channel were able to make better decisions in their increased sensitivity which was caused by the increase in SNR value.

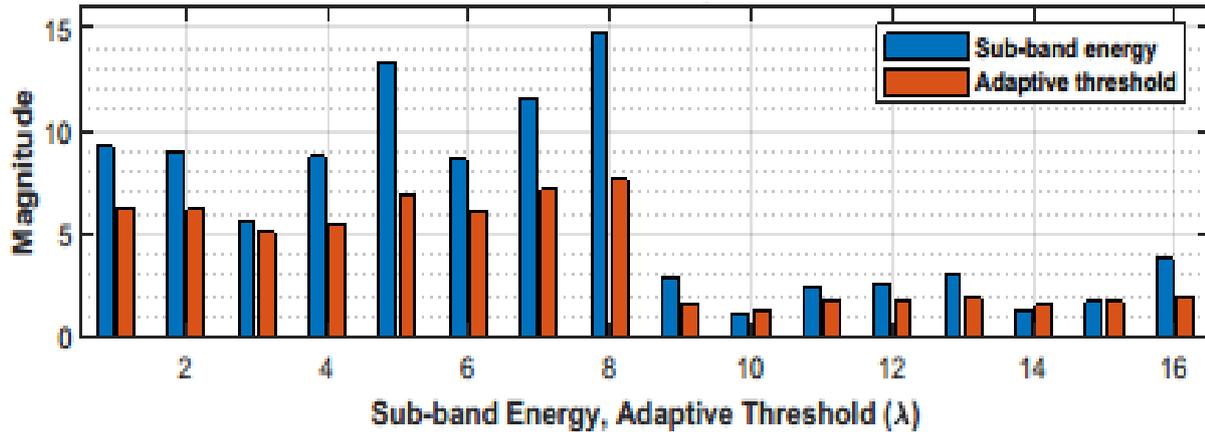


Figure 11: HT-DWPT Spectrum sensing at -5dB

The SNR was increased from $-5dB$ to $0dB$ and the spectrum sensing performance was as shown in Figure 12, where it can be seen that sub-band channels 10, 14, and 15 were identified as vacant. With increase in SNR value, the adaptive thresholds were making better decisions in identifying vacant sub-band channels.

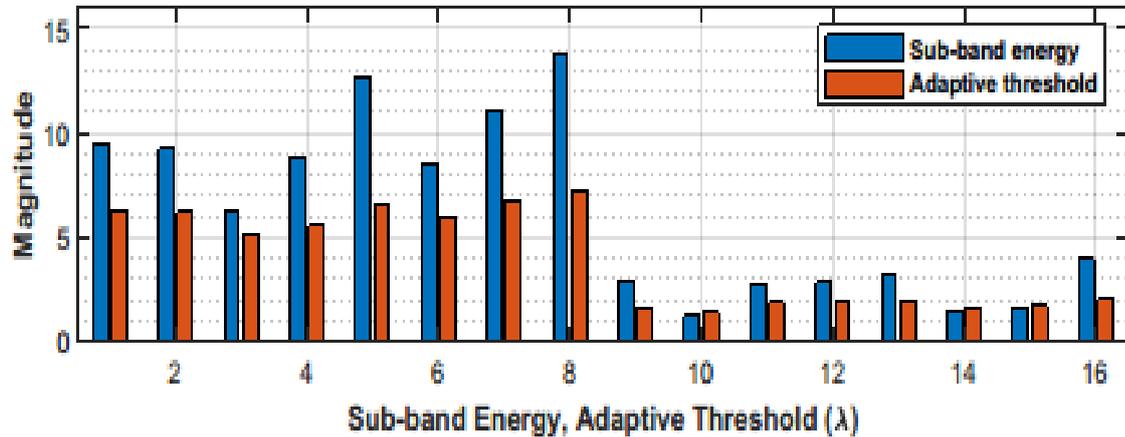


Figure 12: HT-DWPT Spectrum sensing at 0dB

Furthermore, the SNR was increased from $0dB$ to $5dB$ as shown in Figure 13 where sub-band channels 3, 6, 10, 14, and 15 were identified as vacant. Clearly, the increase in SNR made the adaptive thresholds perform better.

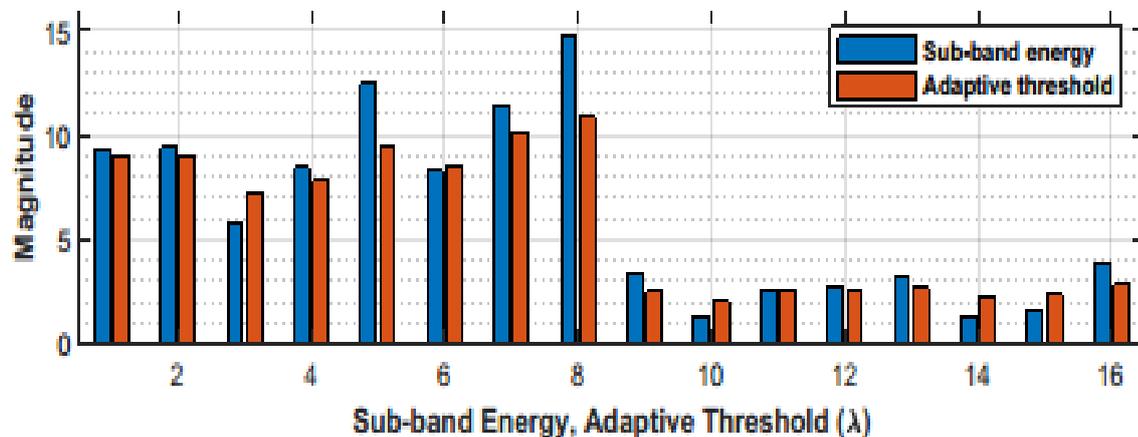


Figure 13: HT-DWPT Spectrum sensing at 5dB

3.5 Receiver Operating Characteristic (ROC) Curves

The performance of the spectrum sensing technique with respect to variation of probability of false (P_{fa}) alarm is shown in Figure 14 where it can be seen that as $P_{fa} \rightarrow 1$, probability of detection (P_d) is increasing. This is an indication of good P_d because as P_{fa} increases, P_d also becomes higher; this is a desirable performance if good spectrum sensing is to be maintained.

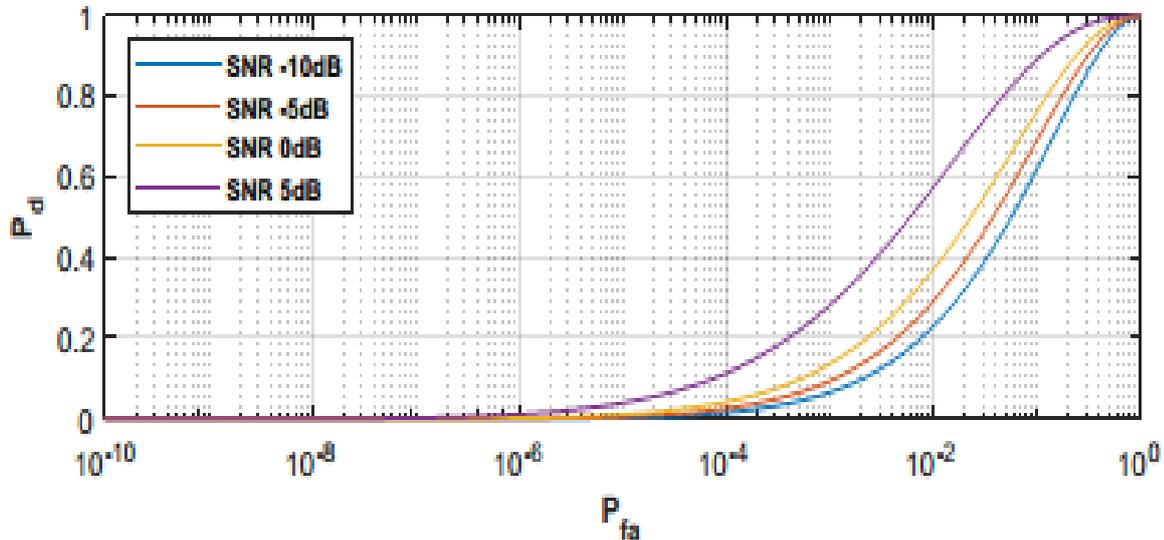


Figure 14: ROC performance for probability of detection versus probability of false alarm

The performance of the spectrum sensing technique can be seen in terms of the variation of SNR as shown in Figure where the increase in SNR values causes an increase in P_d . This performance is not unexpected comparing Figures 10 to 14 are compared. The increase in SNR increases the P_d which is what is expected from the results obtained.

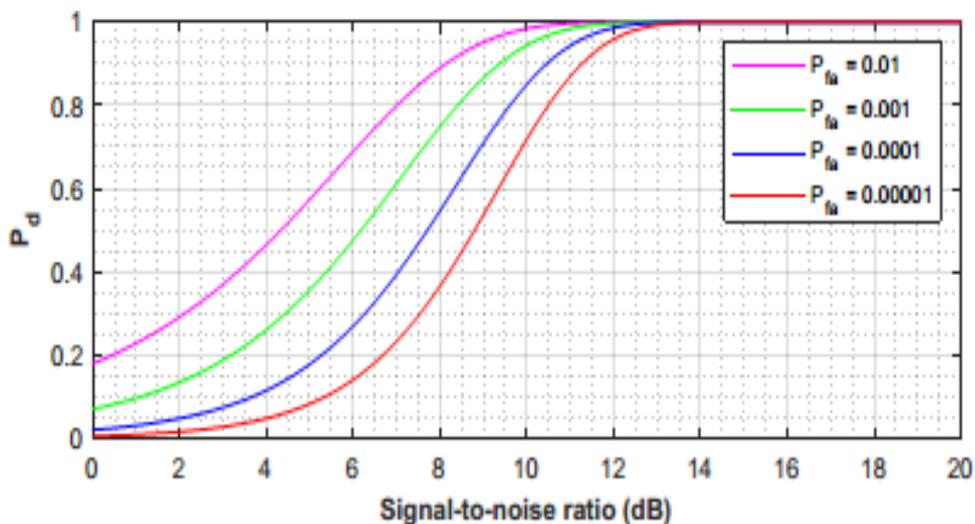


Figure 15: ROC performance for probability of detection versus SNR

The probability of detection against the probability of false alarm was plotted for $-10dB$, $-5dB$, $0dB$ & $5dB$ as presented in Figure 16. In Figure 16a at $-10dB$ both proposed and referred scheme have the same performance this is because of low energy across sub-band channels. It can be seen in Figure 16b that the proposed scheme has better performance at $-5dB$ than the referred scheme, this is because Hilbert Transform has a better ability of detecting sharp changes in the transition of signals. Increasing SNR increases the performance of the proposed scheme as can further be seen in Figures 16c and 16d. This shows the superiority of Hilbert Transform when combined with DWPT in detecting sharp changes in the phase of signals than when DWPT alone is used.

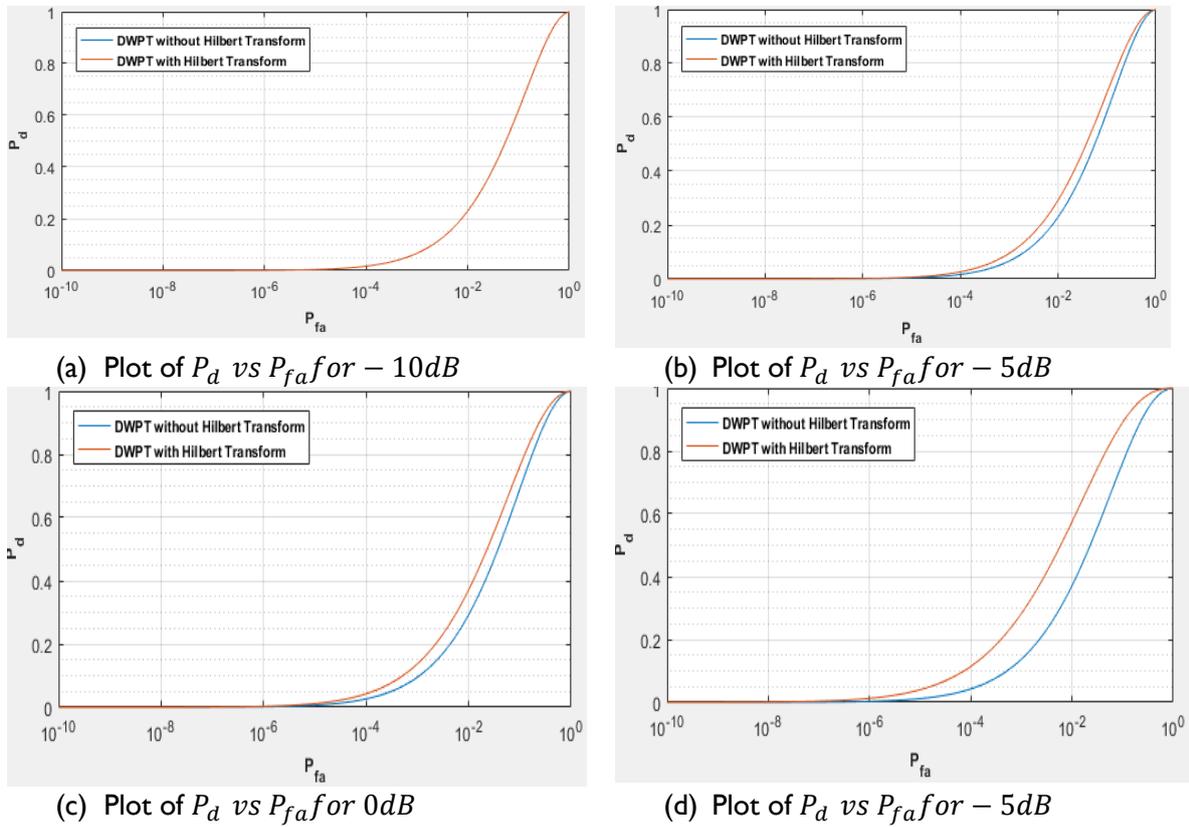


Figure 16: Plots for probability of detection against the probability of false alarm

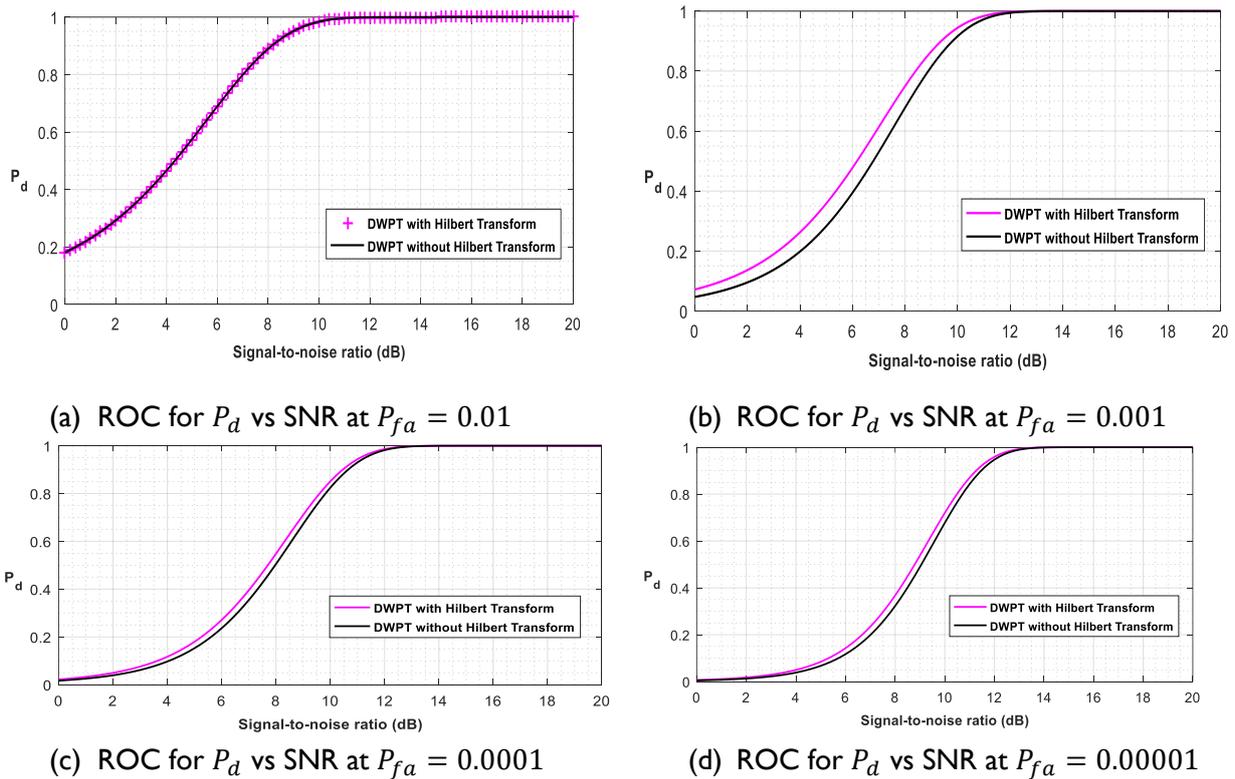


Figure 17: ROC plots for probability of detection against SNR

The ROC plots for probability of detection against SNR for different values are shown in Figure 17. The plots further indicated the proposed method have a better performance result compared to the reference strategy. A summary of performance comparison for DWPT and proposed enhanced HT-DWPT techniques is presented in Table 2.

In summary, although the proposed technique shows a better detection performance ability compared to the reference model, it needs to pay for rather high memory utilization and latency for a high-level decomposition.

Table 2: Summary of performance evaluation metrics for DWPT and HT-DWPT based spectrum sensing

SNR (dB)	DWPT			HT-DWPT		
	No. of Channels detected	P_{fa}	P_d	No. of Channels detected	P_{fa}	P_d
-10	1	0.01	0.2298	1	0.01	0.2298
-5	1	0.001	0.06636	2	0.002	0.136
0	2	0.0002	0.03918	3	0.0003	0.07785
5	3	0.00003	0.0226	5	0.00005	0.08454

4. Conclusion

This research successfully demonstrates that integrating the Hilbert Transform with Discrete Wavelet Packet Transform (DWPT) significantly enhances the performance of wavelet-based spectrum sensing. The hybrid HT-DWPT method provides superior signal representation and improves the probability of detection at low SNR levels, offering a more reliable solution for identifying spectrum opportunities in cognitive radio networks. However, the enhanced performance is achieved with certain practical trade-offs. The primary limitation is the increased computational overhead and memory utilization. The DWPT decomposition itself, especially at higher levels beyond the 4 levels used here, and the subsequent processing of Hilbert Transforms across all sub-bands, introduce greater algorithmic complexity and latency. This could challenge real-time implementation in power-constrained cognitive radio devices, where rapid sensing decisions are critical. Furthermore, while performance improved at SNRs of -5dB and above, detection in extremely noisy environments (below -5dB) remains a practical challenge, limiting applicability in the most severe fading conditions. Regarding real-world applicability, this technique is a strong candidate for infrastructure-based sensing nodes or collaborative sensing networks, where processing resources can be centralized, and the cost of higher computational load is justified by the gains in detection accuracy. The improved probability of detection directly translates to better protection for primary users and more efficient spectrum utilization. To transition this work from simulation to deployment, future research must focus on developing optimized hardware architectures and efficient algorithms to mitigate the computational burden. Additional investigation into the method's performance under real-world, superimposed multi-user signals and across diverse fading channel models is also essential to fully validate its practical robustness.

References

- Abdulsattar, A. Mahmood, A. and Zahir, AH.. 2012. Energy Detection Technique for Spectrum Sensing in Cognitive Radio: A Survey. *International Journal of Computer Networks & Communications* 4 (5): 223-242. <https://doi.org/10.5121/ijcnc.2012.4514>.
- Adoum, BA., Alfateh MAM. and Varun, J. 2010. Discrete Wavelet Packet Transform Based Multiresolution Spectrum Sensing Using Cyclostationary Feature Detector. In *2010 International Conference on Intelligent and Advanced Systems*, 1–6. IEEE. <https://doi.org/10.1109/ICIAS.2010.5716118>.
- Almeida, EPL., Paulo, HPC., Pedro, AABC. and Robson, DV. 2008. Experimental Study of a Wavelet-Based Spectrum Sensing Technique. In *2008 42nd Asilomar Conference on Signals, Systems and Computers*, 1552–1556. IEEE. <https://doi.org/10.1109/ACSSC.2008.5074682>.
- Aloqaily, M., Salameh, HB., Al Ridhawi, I., Batieha, K. and Othman, JB. 2020. A multi-stage resource-constrained spectrum access mechanism for cognitive radio IoT networks: Time-spectrum block utilization. *Future Generation Computer Systems*, 110: 254-266.
- Akyildiz, IF., Kak, A. and Nie, S. 2020. 6G and beyond: The future of wireless communications systems. *IEEE access*, 8:133995-134030.
- Chandran, A., Anantha, AK., Arun, K., Subramania MS., Uma, SI., Ramanathan, R. and Roshini, CN. 2011. Discrete Wavelet Transform Based Spectrum Sensing in Futuristic Cognitive Radios. In *2011 International Conference on Devices and Communications (ICDeCom)*, 1–4. IEEE. <https://doi.org/10.1109/ICDECOM.2011.5738461>.

- Chantaraskul, S. and Klaus, M. 2009. "Implementation of Wavelet Analysis for Spectrum Opportunity Detection." In *2009 IEEE 20th International Symposium on Personal, Indoor and Mobile Radio Communications*, 2310–14. IEEE. <https://doi.org/10.1109/PIMRC.2009.5450129>.
- Chen, J., Gibson, A. and Zafar, J. (2008, September). Cyclostationary spectrum detection in cognitive radios. In *IET Seminar on Cognitive Radio and Software Defined Radio: Technologies and Techniques* pp. 17-1. Stevenage UK: IET. <https://doi.org/10.1049/ic:20080398>.
- Dakshata, P. and Gejji, PV.. 2016. Energy Detection Using Discrete Wavelet Transform in Cognitive Radio System. *IJAREEIE* 5 (6): 5522–28. <https://doi.org/10.15662/IJAREEIE.20156.0506130>.
- Devi, TA. and Sruthi, S. 2014. Discrete Wavelet Packet Transform Based Cooperative Spectrum Sensing for Cognitive Radios. In *2014 First International Conference on Computational Systems and Communications (ICCS)*, 226–231. IEEE. <https://doi.org/10.1109/COMPSC.2014.7032652>.
- Dibal, PY., Onwuka, EN., James, A. and Alenoghena, CO. 2018. Enhanced Discrete Wavelet Packet Sub-Band Frequency Edge Detection Using Hilbert Transform. *International Journal of Wavelets, Multiresolution and Information Processing* 16 (01): 1850009. <https://doi.org/10.1142/S0219691318500091>.
- Gbenga-Ilori, A., Imoize, AL., Noor, K. and Adebolu-Ololade, PO. 2025. Artificial Intelligence Empowering Dynamic Spectrum Access in Advanced Wireless Communications: A Comprehensive Overview. *AI*, 6(6): 126, 1-59
- Gao, Y., Maolin, X., Fengyun, Y., Yachun, M. and Shuang, S. 2015. Improved Wavelet Threshold de-Noiseing Method Based on GNSS Deformation Monitoring Data. *Journal of Engineering & Technological Sciences* 47(4): 463-476.
- Instruments, National. 2019. LabVIEW 2010 Advanced Signal Processing Toolkit Help. 2019. https://zone.ni.com/reference/en-XX/help/371419D-01/lvasptconcepts/wa_cwt/.
- Jeng, SS., Jia-Ming, C., Hong-Zong, L. and Chen-Wan, T. 2011. Wavelet-Based Spectrum Sensing for Cognitive Radios Using Hilbert Transform. *World Academy of Science, Engineering and Technology* 5: 426–30.
- Jiang, ZL., Qin-Yu, Z., Ye, W. and Xue-Quan, S. 2011. Wavelet Packet Entropy Based Spectrum Sensing in Cognitive Radio. In *2011 IEEE 3rd International Conference on Communication Software and Networks*, 293–98. IEEE. <https://doi.org/10.1109/ICCSN.2011.6014054>.
- Jindal, S., Dhananjay, D. and Ranjan, G. 2014. Wavelet Based Spectrum Sensing in a Multipath Rayleigh Fading Channel. In *2014 Twentieth National Conference on Communications (NCC)*, 1–6. IEEE. <https://doi.org/10.1109/NCC.2014.6811292>.
- Iqbal, A., Nauman, A., Qadri, YA. and Kim, SW. 2025. Optimizing Spectral Utilization in Healthcare Internet of Things. *Sensors*, 25(3): 1-25.
- Kang, AS., Sharma, V. and Singh, JS. 2017. Efficient Spectrum Sensing Using Discrete Wavelet Packet Transform Energy Detection in Cognitive Radio. *Advances in Wireless and Mobile Communications*, 10(2): 193-212.
- Kim, K., Yan, X., and Sampath, R. 2010. Energy Detection Based Spectrum Sensing for Cognitive Radio: An Experimental Study. In *2010 IEEE Global Telecommunications Conference GLOBECOM 2010*, 1–5. IEEE. <https://doi.org/10.1109/GLOCOM.2010.5683560>.
- Kim, S., Youngwoo, Y., Hyungsuk, J., Minjae, K. and Hyuckjae, L. 2008. Selective Discrete Wavelet Packet Transform-Based Energy Detector for Cognitive Radios. In *MILCOM 2008-2008 IEEE Military Communications Conference*, 1–6. IEEE. <https://doi.org/10.1109/MILCOM.2008.4753628>.
- Li, H., and Jing, L. 2015. Wavelet Transforms Detection of Spectrum Sensing in the Space Network. In *2015 Science and Information Conference (SAI)*, 978–84. IEEE. <https://doi.org/10.1109/SAI.2015.7237261>.

Liu, Y., Zhangdui, Z., Gongpu, W. and Dan, Hu. 2015. Cyclostationary Detection Based Spectrum Sensing for Cognitive Radio Networks. *J. Commun.* 10 (1): 74–79. <https://doi.org/10.12720/jcm.10.1.74-79>.

López-Benítez, M. and Fernando, C. 2012. Improved Energy Detection Spectrum Sensing for Cognitive Radio. *IET Communications* 6 (8): 785–96. <https://doi.org/10.1049/iet-com.2010.0571>.

Vithalani, AA. and Vithalani, CH. 2021. Optimization of Spectrum Sensing Technique in Cognitive Radio. PhD Thesis Gujarat Technological University Ahmedabad.

Panaitopol, D., Rohit, D., and Gerhard, F. 2012. Cyclostationary Detection of Cognitive Radio Systems Using GFDM Modulation. In *2012 IEEE Wireless Communications and Networking Conference (WCNC)*, 930–34. IEEE. <https://doi.org/10.1109/WCNC.2012.6214508>.

Poor, HV. 2013. *An Introduction to Signal Detection and Estimation*. Springer Science & Business Media.

Qin, Z., Nan, W., Yue, G. and Laurie, C. 2012. Adaptive Threshold for Energy Detector Based on Discrete Wavelet Packet Transform. In *Wireless Telecommunications Symposium 2012*, 1–5. IEEE. <https://doi.org/10.1109/WTS.2012.6266117>.

Sarker, M. 2016. Hilbert Transform Based Edge Detection Approach for Wideband Spectrum Sensing in Cognitive Radios. In *2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, 2274–2278. IEEE. <https://doi.org/10.1109/WiSPNET.2016.7566547>.

Sawant, MSS. and Kumbhar, MS. 2012. Wavelet Packet Transform Based Energy Detector for Spectrum Sensing. *International Journal of Emerging Technology and Advanced Engineering*, 2(3): 379-382.

Varadharajan, E. and Rajkumari, M. 2012. Discrete Wavelet Transform Based Spectrum Sensing in Cognitive Radios Using Eigen Filter. *IJAET* 3 (1): 389–91.

Wu, J., Tao, L. and Guangxin, Y. 2009. An Energy Detection Algorithm Based on Double-Threshold in Cognitive Radio Systems. In *2009 First International Conference on Information Science and Engineering*, 493–96. IEEE. <https://doi.org/10.1109/ICISE.2009.257>.

Zhang, L., Liang, YC. and Xiao, M. 2018. Spectrum sharing for Internet of Things: A survey. *IEEE Wireless Communications*, 26(3): 132-139.